

## Research Article

# Comparative Study of Basic Time Domain Time-Delay Estimators for Locating Leaks in Pipelines

Vladimir A. Faerman<sup>1\*</sup>, Valeriy S. Avramchuk<sup>2</sup>

<sup>1</sup>Department of Complex Information Security of Computer Systems, Tomsk State University of Control Systems and Radioelectronics, 40 Lenina pr. Tomsk 634050, Russia

<sup>2</sup>Department of Automation and Robotics, Tomsk Polytechnic University, 4 Lenina str., Tomsk 634028, Russia

### ARTICLE INFO

#### Article History

Received 14 October 2019

Accepted 22 October 2019

#### Keywords

Cross-correlation  
 leak detection  
 leak noise correlator  
 passive TDE scenario  
 phase spectrum  
 time-delay estimation  
 time-domain methods

### ABSTRACT

The article is devoted to a survey of the known basic Time-Delay Estimation (TDE) methods in the application for detecting fluid leaks in pipeline transport and distribution systems. In the paper, both active and passive estimation methods are considered with respect to the presented generalized classification. However, the main attention is paid to the study of passive methods and their algorithmic implementation. Among the passive methods the Absolute Difference Function (ADF) minimizing algorithms, the Basic Cross-Correlation (BCC) algorithm, the adaptive Least Mean Square (LMS) filtering algorithm are implemented, investigated and compared using a mathematical model of a leak noise signal. All the algorithms are described and the results of the comparison are provided. The advantage of the LMS algorithm in processing the noisy signals is shown. However, its implementation requires choosing a convergence parameter. The necessity in choice of the additional parameter makes the LMS algorithm less practically applicable than the BCC algorithm. The ADF algorithm showed the lowest noise resistivity and can be considered as useful for signal detection, but not for TDE. Some conclusions regarding algorithms' use for solving the problem of locating leaks are stated. In particular, correlation-based TDE algorithms, as generalized cross-correlation and time-frequency cross-correlation, appear to be the best choice for the implementation of leak detection software.

© 2020 The Authors. Published by Atlantis Press SARL.

This is an open access article distributed under the CC BY-NC 4.0 license (<http://creativecommons.org/licenses/by-nc/4.0/>).

## 1. INTRODUCTION

The problem of Time-Delay Estimation (TDE) is of great theoretical and practical importance and can be observed in various science and technology fields. The latter is connected with the fact that generally the delay is the time interval between the appearance of some event in one part of the system and its registration in another part of the system. Besides, it is an integral element of dynamic models of physical, chemical, biological, technical and economic systems [1]. However, TDE applications in radio engineering, hydroacoustics, seismology and, especially, in non-destructive testing [1,2] are in the scope of this paper.

The problem of leak location out of a pipeline under pressure, described in detail in Fuchs and Riehle [3], is normally classified as an application in the field of non-destructive testing. The significance of the presented task is beyond any doubt and is due to both the colossal volume of pipelines in operation, and the impossibility of infrastructure's continuous updating.

The physical basis of the method of determining the leak position is the receiving and processing of an acoustic signal emitted by the leak to the pipe. Remote sensors, located on both sides of the supposed leak, register this signal. However, because the signal is propagated in both directions at the same speed, the time delay between

the measured signals on each side of the pipe section can be used to determine the position of the leak, using

$$d_{A,B} = \frac{d_0 \pm T_d \cdot V}{2},$$

where  $r_0$  is a distance between sensors  $A$  and  $B$ ;  $T_d$  is a Time Difference of Arrival (TDOA);  $V$  is sound propagation velocity;  $d_A, d_B$  are distances from the leak to sensors  $A$  and  $B$ , respectively.

Currently, a significant number of methods and algorithms of Digital Signal Processing (DSP) have been developed to solve the TDE problem. Active and passive classes of TDE methods could be distinguished depending on the specifics of the problem being solved [4]. Active methods, in contrast to passive ones, suggest the possibility of emitting a specific special signal in a dynamic system. The parameters of the signal are assumed to be determined *a priori*. Although the paper focuses on the study of passive TDE methods [3] used to locate leaks, active methods are also briefly discussed in the subsequent section. The discussion is essential for a better understanding of the peculiarities and algorithmic implementation of the passive methods [5,6].

## 2. CLASSIFICATION OF TDE METHODS

In this section, some well-known TDE methods for various passive and active scenarios are discussed, and their classification is

\*Corresponding author. Email: [faermanvlad@mail.ru](mailto:faermanvlad@mail.ru)

presented. As noted earlier, TDE methods can be divided into active and passive according to their field of use and the mathematical problem statement.

### 2.1. Passive and Active TDE Scenarios

The generalized TDE task definition is described by the expression [4]

$$\begin{cases} S_A(t) = W_A(p) \cdot u(t) + n_A(t), \\ S_B(t) = W_B(p) \cdot u(t - T_d) + n_B(t), \end{cases} \quad (1)$$

where  $u(t)$  is the deterministic signal;  $n_A(t)$  and  $n_B(t)$  are random noise signals;  $y_A(t)$  and  $y_B(t)$  are received signals;  $T_d$  is the TDOA of informative signal components  $y_A(t)$  and  $y_B(t)$ ;  $W_A(p)$  and  $W_B(p)$  are dynamics of a linear system without time-delay. Thus, the task itself is reduced to finding value  $\hat{T}_d$ , the estimated value of time-delay  $T_d$ .

The task of active TDE takes place under conditions of  $n_A(t) = 0$  and  $W_A(p) = 1$  [4]. In the observed case, Eq. (1) will take the form of

$$\begin{cases} y_A(t) = u(t), \\ y_B(t) = W_B(p) \cdot u(t - T_d) + n_B(t). \end{cases} \quad (2)$$

Non-random signal  $u(t)$  is a priori known and is called the reference signal. Otherwise, if signal  $u(t)$  is not a priori available, the passive TDE problem takes place [7].

It is notable that for locating leaks and some other practical applications it is possible to use an intruder seismic detection. In this case the source of the signal  $u(t)$  is within the system. At the same time the impossibility of receiving the signal, generated directly by the object in the system, is assumed [8] to be an active TDE scenario.

### 2.2. Main Classes of TDE Methods

Various approaches and algorithms based on them can be applied to solve the TDE problem. Thus, as it is presented in Björklund [4], TDE methods can be divided into the following groups:

- Time-delay approximation methods;
- Explicit time-delay estimation methods;
- Area and moment statistics methods.

The features, advantages and disadvantages of the described classes of methods are summarized in Table 1. Figure 1 shows a more detailed classification of TDE methods [4].

Table 1 | Classes of TDE methods

Class	Description and Features		
	Theoretical basis	Advantages	Disadvantages
Time-delay approximation methods	Methods are based on the comparison and analysis of signals $y_A(t)$ and $y_B(t)$ , represented in the time-domain or frequency-domain. It is not directly a parameter of a formalized object model. $T_d$ itself is not a parameter of a formalized object model.	No a priori information about the object is required. Applicable to passive and active scenarios.	The accuracy of the estimate is strongly influenced by noise. The choice of an efficient approximation algorithm is determined by the task.
Explicit TDE methods	Methods involve the determination of the $\hat{T}_d$ value as one of the unknown parameters of a dynamic object mathematical model, usually represented in the form of a transfer function.	Most effective in identifying objects with a time delay.	Methods are active and require a priori knowledge of the object. Designed only for objects of the first, second and third order.
Area, moment and statistical methods	Methods are based on the established relationship between the type of transient response $s(t)$ of the system or its impulse response and the $T_d$ value.	Allow suppressing random noises with symmetric probability density.	Difficult to implement since they require to define $s(t)$ or $h(t)$ .

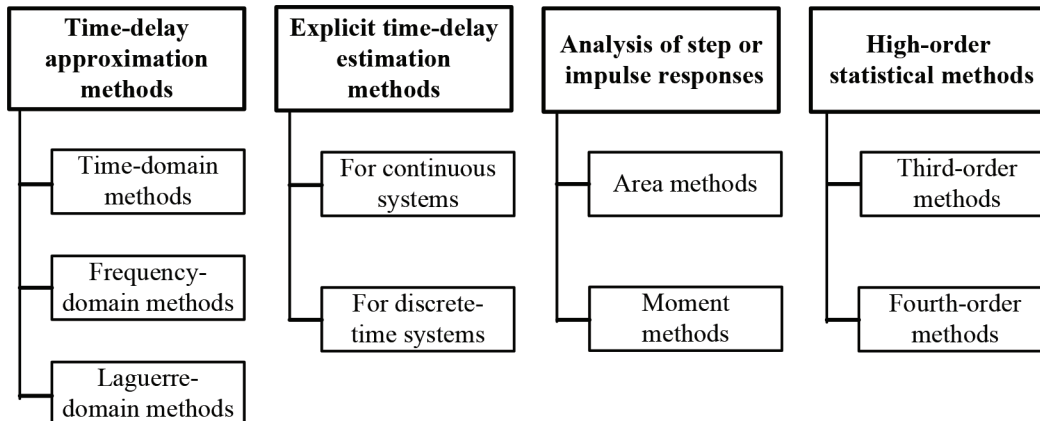


Figure 1 | Classes of TDE methods.

Methods belonging to the first class, especially time-domain [3,8–10] and frequency-domain [10,11], are widely used to solve the problem of the leak location. The methods presented in other groups are more related to the problem of identifying dynamic objects and are used in control science [4]. The methods, including high-order ones, based on the analysis of the system step response or impulse response are also active [1].

Based on the current practice of locating leaks [3,12], all the TDE algorithms can also be provisionally classified into two groups—correlation-based and non-correlation-based. Both frequency and time methods can be classified within the first group, while most of the non-correlation methods can be considered as time-domain.

### 3. IMPLEMENTATION OF BASIC TIME DOMAIN TDE METHODS

For further comparison, descriptions and algorithmic implementations of three different time-domain TDE methods are presented. All three considered methods are passive [9] and are suitable for the leak locating purposes. These methods are considered to be the basic [8,9]. Although algorithms used in locating actual leaks are more complex, they have their advantages and disadvantages.

It should be noted that averaging over segments is used to improve the analysis accuracy by increasing the amount of input data [13]. The total number  $N_0$  of ticks available in sampled signals is given by

$$N_0 = Q \cdot N,$$

where  $Q$  is the number of data segments,  $N$  is the number of samples in each data segment.

#### 3.1. ADF Minimizing Algorithm

One of the simplest time-domain methods is the non-correlation method of minimizing an Absolute Difference Function (ADF) [8]. The scheme of the method is presented in Figure 2. The following notations are used to describe the algorithms:  $s_A(t_i)$ ,  $s_B(t_i)$  are the analyzed signals represented by a series of sampled values; TD is the block of the signal time delay for time  $\tau_j$ ,  $q$  is the index of the data segment. Being discrete,  $t_i$  and  $\tau_j$  are multiples of sampling interval  $\Delta t$

$$\begin{aligned} t_i &= i \cdot \Delta t, & i &= 0, 1, \dots, N-1, \\ \tau_j &= j \cdot \Delta t, & j &= -\frac{N}{2}, -\frac{N}{2} + 1, \dots, \frac{N}{2} - 1. \\ q &= 0, 1, \dots, Q-1. \end{aligned}$$

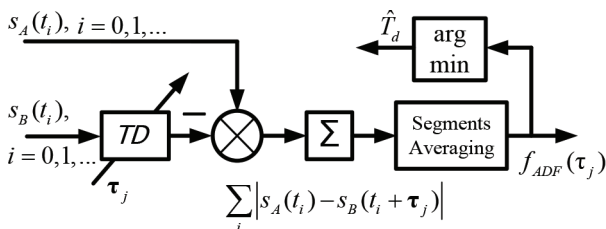


Figure 2 | Scheme of TDE via minimizing ADF.

The TDA algorithm implies minimization of the difference function between the channel signals shifted in time as follows:

$$f_{ADF}^{(q)}(\tau_j) = \begin{cases} \frac{1}{N-j} \cdot \sum_{i=|j|}^{N-1} |s_A(t_i) - s_B(t_i + \tau_j)|, & \tau_j < 0, \\ \frac{1}{N-j} \cdot \sum_{i=0}^{N-j} |s_A(t_i) - s_B(t_i + \tau_j)|, & \tau_j \geq 0. \end{cases} \quad (3)$$

$$f_{ADF}(\tau_j) = \sum_{q=0}^{Q-1} f_{ADF}^{(q)}(\tau_j),$$

$$\hat{T}_d = \arg \min(f_{ADF}(\tau_j)).$$

The advantage of this method is computational simplicity and high efficiency of signal detection, but not an optimal estimate of the delay time, especially when the signal is very noisy or distorted [4].

At the same time, the implementation of more complex but similar methods based on the selection of several signals parameters in addition to time delay requires complex calculations. Moreover, the lack of a priori information about the pipeline condition and configuration normally does not allow choosing the proper optimization parameters, which not only affects the locating accuracy but also makes such approximations methods inapplicable at all [14,15].

#### 3.2. BCC Algorithm

Methods based on the calculation and analysis of the cross-correlation function have gained widespread recognition among time-domain TDE algorithms [7]. The procedure is based on the determination of the correlation coefficient between the channels signals, one of which is time-shifted [8]. A simple Basic Cross-Correlation (BCC) TDE scheme [16] is presented in Figure 3.

The algorithm shown in the scheme above is given by

$$r_{BCC}^{(q)}(\tau_j) = \begin{cases} \frac{1}{N-j} \cdot \sum_{i=|j|}^{N-1} |s_A(t_i) \cdot s_B(t_i + \tau_j)|, & \tau_j < 0, \\ \frac{1}{N-j} \cdot \sum_{i=0}^{N-j} |s_A(t_i) \cdot s_B(t_i + \tau_j)|, & \tau_j \geq 0. \end{cases} \quad (4)$$

$$r_{BCC}(\tau_j) = \sum_{q=0}^{Q-1} r_{BCC}^{(q)}(\tau_j),$$

$$\hat{T}_d = \arg \max(r_{BCC}(\tau_j)).$$

Despite the obvious similarity between Eqs. (3) and (4), their application features differ significantly. Calculations in Eq. (4) require performing only operations of additions and in the absence of high accuracy requirements, can be effectively performed by most computing devices, including microprocessors [17,18]. The efficient calculations require a hardware implementation of the

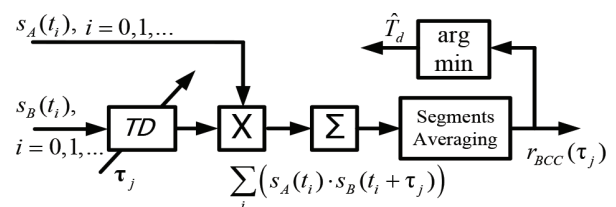


Figure 3 | Scheme of TDE via BCC.

multiplication block with accumulation (multiplier-accumulator). This type of circuit is traditionally considered to be a DSP specific attribute [19].

A more effective correlation method implementation for TDE is the use of generalized cross-correlation algorithms. It differs from the described BCC algorithm by preprocessing [20] of the signals on inputs of the correlator. At the moment, the generalized correlation analysis is considered as the main tool for the acoustic method of locating leaks [10,21].

### 3.3. Algorithm with the Adaptive LMS Filter

An alternative TDE method [22] is the use of a Finite Impulse Response (FIR) filter. A distinctive feature of the TDE method is the need for iterative refinement of filter coefficients, which makes this solution adaptive. In this case, the resulting solution is for minimizing the root-mean-square error [22,23].

The TDE scheme demonstrating the use of an adaptive filter is presented in Figure 4.

The algorithm with the adaptive Least Mean Square (LMS) filter is given by [23]

$$\begin{aligned} \varepsilon^{(n)} &= s_A(t_0^{(n)}) - \sum_{j=-N/2}^{N/2-1} w^{(n)}(\tau_j) \cdot s_B(t_0^{(n)} + \tau_j), \\ w^{(n+1)}(\tau_j) &= w^{(n)}(\tau_j) + \mu \cdot \varepsilon^{(n)} \cdot s_B(t_0^{(n)} + \tau_j). \end{aligned} \quad (5)$$

In Eq. (5) the following notations are used:  $w^{(n)}(\tau_j)$  are FIR coefficients of the filter at the  $n$ th iteration;  $\varepsilon^{(n)}$  is error at the  $n$ th iteration;  $t_0^{(n)}$  is the time reference to which the coefficients are relatively adjusted at the  $n$ th iteration ( $t_0^{(n)} = t_\gamma, \gamma \in [N/2, N \cdot (Q-1/2)]$ );  $\mu$  is a constant coefficient that determines the rate of filter adjustment (fixed at  $1/N$ ).

The lag time is estimated by analyzing the FIR filter coefficients after their preliminary averaging

$$\begin{aligned} f_{LMS}(\tau_j) &= w(\tau_j) = \sum_n k_n \cdot w^{(n)}(\tau_j), \\ \hat{T}_d &= \arg \max(w(\tau_j)). \end{aligned} \quad (6)$$

Let us note that, assuming convergence (5), it is worth choosing coefficients  $k_n$  in (6) in such a way that

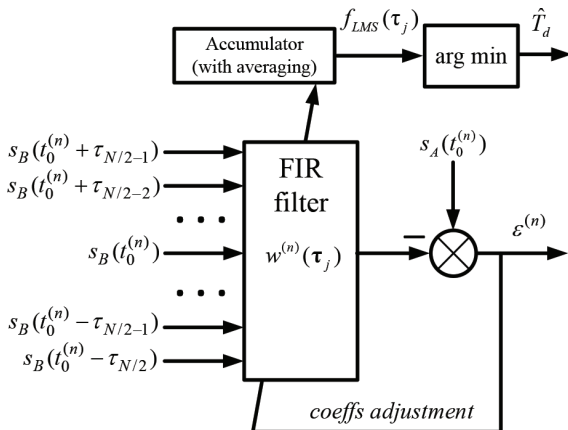


Figure 4 Scheme of TDE with the adaptive LMS filter.

$$k_n \in [0, 1], k_{n-1} \leq k_n \leq k_{n+1}.$$

The algorithm distinctive feature is applicability and flexibility concerning the amount of input data. In particular, (5) allows processing any amount of newly received data without accumulating  $N$  samples in the buffer. The number of necessary iterations is determined by convergence factor  $\mu$ . To ensure the comparability in the number of computational operations among studied algorithms given by Eqs. (3) and (4), the following assumption was made

$$\gamma = (Q-1) \cdot n, n = 0, 1, \dots, N-1.$$

### 3.4. Features of Frequency-Domain TDE

It is known that the temporal and frequency representations of the signal are equivalent in terms of information content [24]. The information about the time lag can be obtained in the frequency domain by determining the phase shift between channel signals [25,26].

From the perspective of the algorithmic implementation, phase response analysis is a complex task, various solutions of which are proposed in Piersol [11], Zhen, and Zi-qiang [24], and Terentiev and Firsov [27]. The algorithmic implementation and comparison of various approaches to TDE based on analysis of the shape of the phase curve are the subject of a separate study and are not considered in this paper.

## 4. RESULTS AND DISCUSSION

The series of simulations were conducted to compare the ADF, BCC and LMS filtering algorithms for locating pipeline leaks. Signals were generated by software using the leak noise model described further in the corresponding subsection.

In the prospective study  $N$  was taken to be consistently equal to 1024, 2048, 4096 and 8192,  $Q$  was taken to be 5 in all cases presented below. The values of  $N$  and  $Q$  were chosen both to utilize the realistic size of the leak noise samples [27] and to provide clear results of the comparison. The sampling interval was assumed to be 44100 Hz.

### 4.1. Leak Noise Model

The leak noise model is based on the models of additive noise emission [28] and sound propagation along a pipe [29], respectively. According to Brennan et al. [29], to simulate the leak noise signals received by the sensors, the uniformly distributed noise-like signal was processed by pipe filters with dynamic characteristics  $H_{A,B}(f, d_{A,B})$  given by

$$\begin{aligned} H_{A,B}(f, d_{A,B}) &= e^{-2\pi \cdot f \cdot \beta \cdot d_{A,B}} \cdot e^{-i2\pi \cdot f \cdot \frac{d_{A,B}}{V}}, \\ V &= \frac{V_0}{\sqrt{1 + \frac{2 \cdot B \cdot R}{E \cdot h}}}, \beta = \left( \frac{2 \cdot B \cdot R}{10 \cdot E \cdot h} \right) / \left( V \cdot \sqrt{1 + \frac{2 \cdot B \cdot R}{E \cdot h}} \right), \end{aligned}$$

where  $d_A, d_B$  are distances from the leak to the sensors,  $B$  is the bulk modulus of the fluid,  $V_0$  is free-field wave-speed in the liquid,  $R$  is the mean radius of the pipe,  $h$  is wall thickness,  $E$  is Young's modulus of pipe material,  $V$  is the speed of the leak noise propagation,  $\beta$  is the attenuation factor.

The amplitude–frequency response (AFR) of the noise-free test signals is shown in Figure 5. The scale of the graphs along the vertical axis is normalized by the maximum values.

The additive noise corrupting the leak noise signal is based on empirical results presented in Papastefanou et al. [28]. Figure 6 shows both AFR and the amplitude envelope of the synthesized noise signals. The intensity of the noise superimposed on the test signals was determined by the target Signal-to-Noise Ratio (SNR). In determining the SNR, the channel with higher intensity of the noise-free signal was taken into account. However, the noise of an identical intensity was superimposed on each of the channels.

Let us note that the featured leak noise model has its limitations. First, it is not accurate for metal pipes because it is based on the pipe filter that is developed mostly for plastic pipes [29]. Second, the model does not take into account the impact of cavitation [27] and some other effects on emitted acoustic signals. However, the model qualitatively simulates leak noise signals and is relevant for using in the comparative study of the TDE methods. Faerman and Tsavnin [30] discusses the use of the leak noise model and its limitations in more detail.

### 4.2. Comparison of TDE Algorithms

To compare the ADF, BCC and LMS filtering algorithms, peak-to-mean values were used, which were SNR estimates of the signals at the output of the TDE device [31], calculated according to

$$I_{ADF} = \frac{\max(f'_{ADF}(\tau_j))}{\text{RMS}(f'_{ADF}(\tau_j))}, \tag{7}$$

$$f'_{ADF}(\tau_j) = f(\tau_j) - E(f(\tau_j)),$$

$$f(\tau_j) = \max(f_{ADF}(\tau_j)) - f_{ADF}(\tau_j);$$

$$I_{BCC} = \frac{\max(r_{BCC}(\tau_j))}{\text{RMS}(r_{BCC}(\tau_j))}; \tag{8}$$

$$I_{LMS} = \frac{\max(f_{LMS}(\tau_j))}{\text{RMS}(f_{LMS}(\tau_j))}, \tag{9}$$

where RMS is root mean square,  $E$  is mean value.

TDE error was evaluated according to the formula

$$\text{Err} = \left| \hat{T}_d - \frac{r_A - r_B}{V} \right|. \tag{10}$$

Functions at the output of TDE devices for different  $N$  and SNR are in Figs. 7 and 8. The scale of the graphs along the vertical axis is maximized.

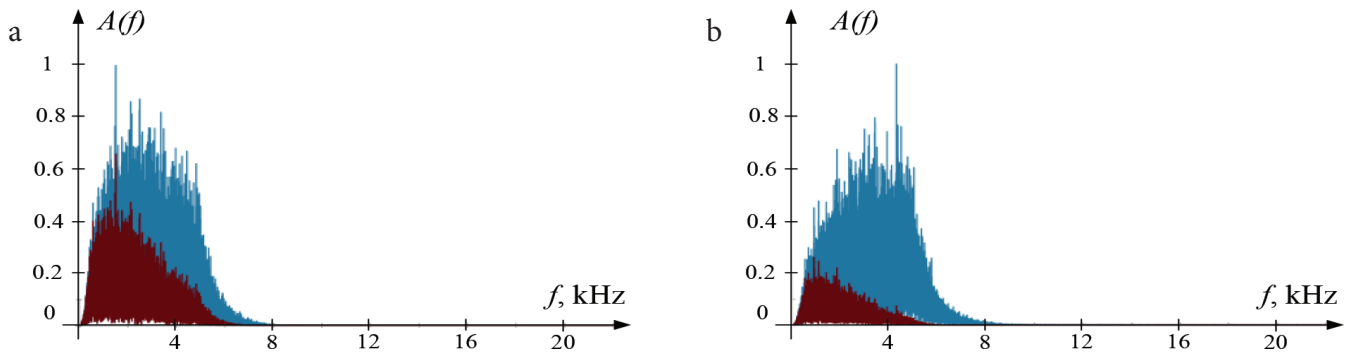


Figure 5 | Amplitude–frequency response of test signals (channel A is in red, channel B is in blue). The model of the water supply steel pipe with a mean radius of 84 mm and a wall thickness of 4 mm is used: (a) distances to sensors A and B are 18 and 11 m, respectively; (b) distances to sensors A and B are 22 and 7 m, respectively.

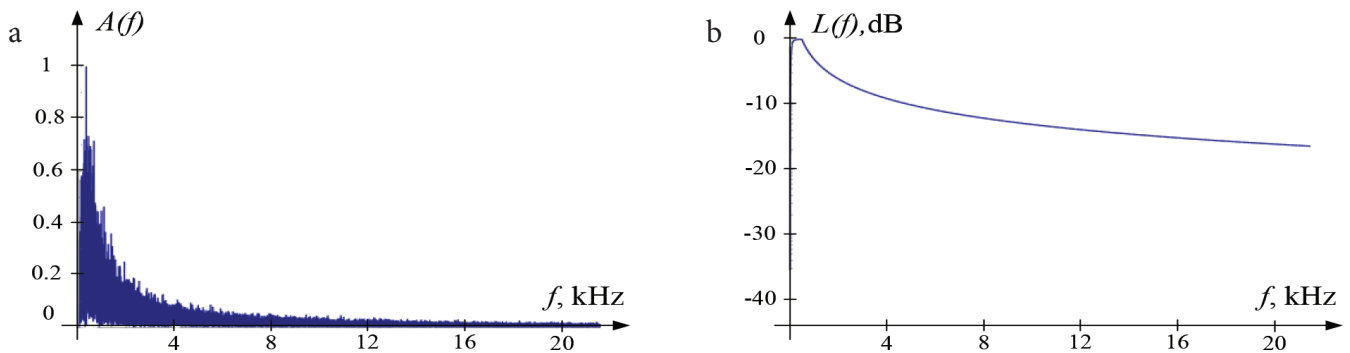


Figure 6 | Spectral characteristics of additive noise signals: (a) AFR and (b) amplitude envelope in logarithmic scales.

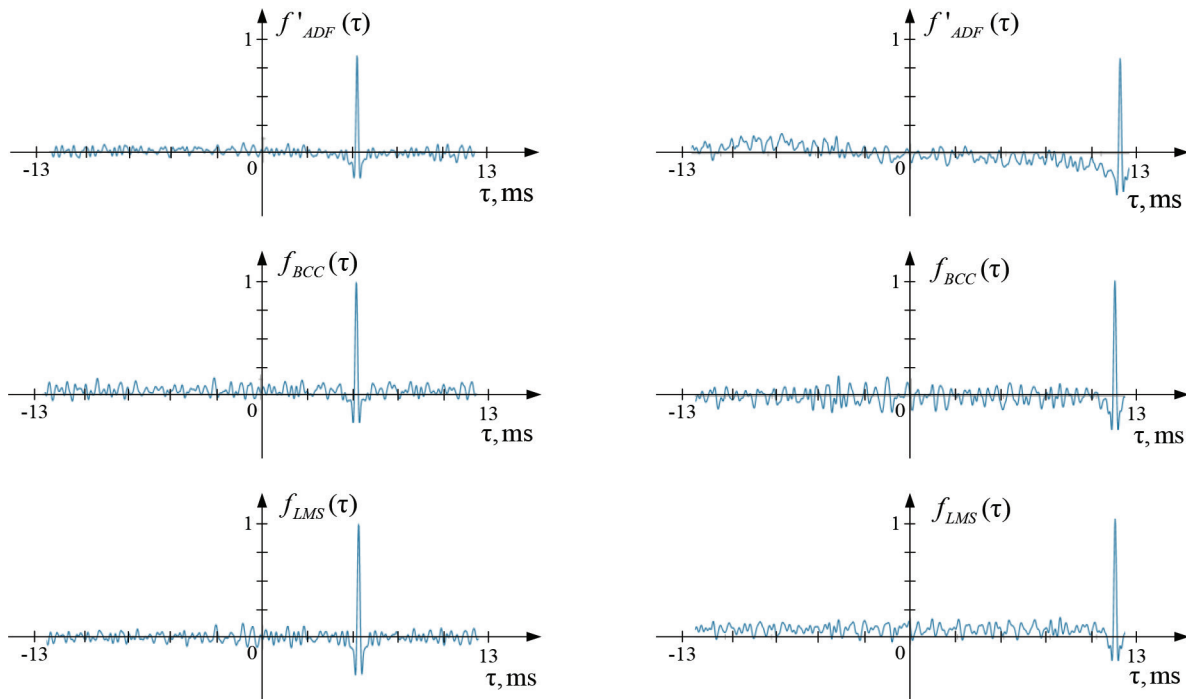


Figure 7 | TDE output signals. On the left: signal A (Fig. 5a),  $N = 1024$ , no noise. On the right: signal B (Fig. 5b),  $N = 1024$ , no noise.

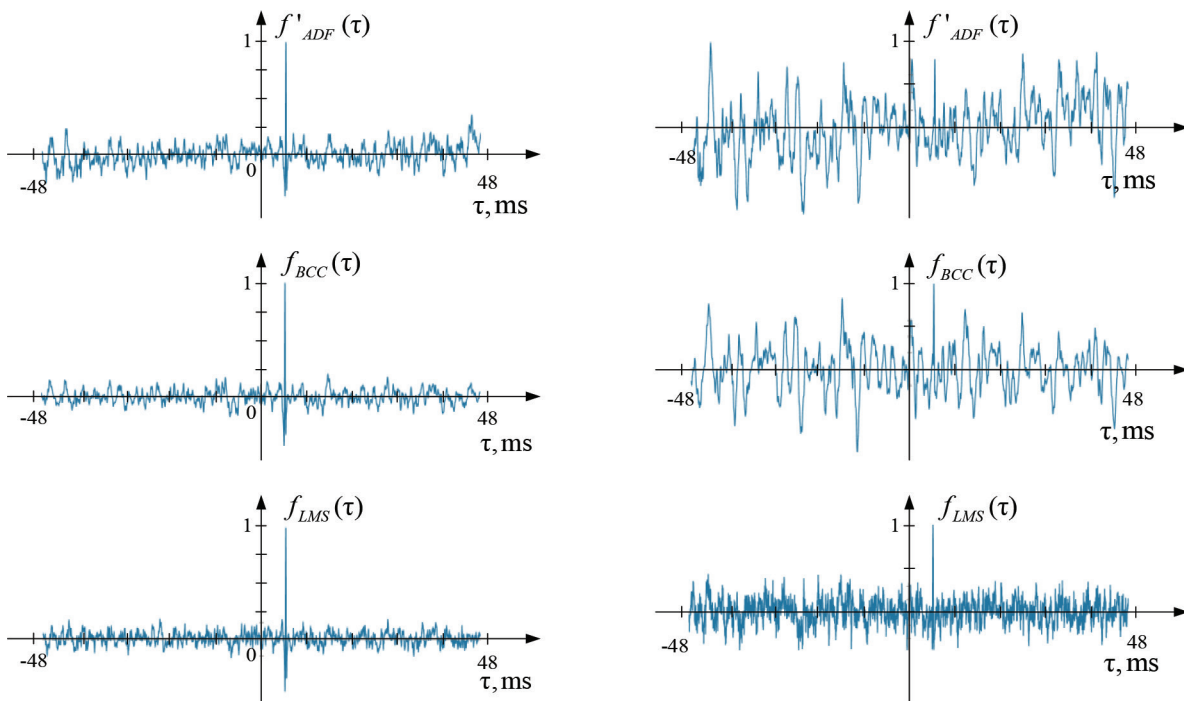


Figure 8 | TDE output signals. On the left: signal A,  $N = 4096$ , SNR = 1. On the right: signal A,  $N = 4096$ , SNR = 0.4.

The results of the experiments for different  $N$  and SNR are summarized in Tables 2 and 3. In both tables, a single asterisk “\*” marks the results where the maximum value at the TDE output is due to the noise influence. A double asterisk “\*\*” marks the results where the detected true maximum of the function is not the only one and there are false peaks of the comparable magnitude.

### 4.3. Outcomes and Prospects

The dependences of the SNR signals at the output of estimators on  $N$  (Figure 9) and on the SNR of the input signals are constructed based on the study (Figure 10).

**Table 2** | Results of TDE for various sizes of data segment (signal in Figure 5a)

SNR	N	ADF TDE		BCC TDE		LMS TDE	
		Err (ms)	$I_{ADF}$	Err (ms)	$I_{BCC}$	Err (ms)	$I_{LMS}$
Inf	1024	<0.023	13.905	<0.023	12.303	<0.023	11.909
	2048	<0.023	18.842	<0.023	17.648	<0.023	16.754
	4096	<0.023	25.924	<0.023	25.161	<0.023	23.943
	8192	<0.023	37.883	<0.023	35.536	<0.023	34.024
5	1024	<0.023	13.610	<0.023	12.149	<0.023	11.675
	2048	<0.023	18.471	<0.023	17.446	<0.023	16.547
	4096	<0.023	25.505	<0.023	24.849	<0.023	23.658
	8192	<0.023	36.825	<0.023	35.249	<0.023	33.593
2	1024	<0.023	11.687	<0.023	10.742	<0.023	10.968
	2048	<0.023	15.592	<0.023	15.747	<0.023	15.153
	4096	<0.023	20.514	<0.023	20.950	<0.023	22.543
	8192	<0.023	31.492	<0.023	32.380	<0.023	29.339
1	1024	<0.023	5.057	<0.023	5.560	<0.023	7.024
	2048	<0.023	6.202	<0.023	8.093	<0.023	10.629
	4096	<0.023	11.370	<0.023	15.901	<0.023	13.640
	8192	<0.023	17.993	<0.023	21.558	<0.023	22.937
0.4	1024	12.228*	2.317	2.566*	3.974	<0.023**	3.885
	2048	11.809*	2.683	<0.023**	2.758	<0.023	5.506
	4096	27.647*	2.655	3.089*	3.583	<0.023	6.846
	8192	76.105*	3.798	<0.023**	3.171	<0.023	9.575

**Table 3** | Results of TDE for various sizes of data segment (signal in Figure 5b)

SNR	N	ADF TDE		BCC TDE		LMS TDE	
		Err (ms)	$I_{ADF}$	Err (ms)	$I_{BCC}$	Err (ms)	$I_{LMS}$
Inf	1024	<0.023	12.554	<0.023	11.457	<0.023	10.292
	2048	<0.023	15.053	<0.023	17.560	<0.023	15.521
	4096	<0.023	20.115	<0.023	25.276	<0.023	22.754
	8192	<0.023	29.649	<0.023	< 0.023	<0.023	33.172
5	1024	<0.023	11.147	<0.023	10.389	<0.023	9.867
	2048	<0.023	13.684	<0.023	16.624	<0.023	14.731
	4096	<0.023	18.241	<0.023	24.326	<0.023	21.703
	8192	<0.023	27.883	<0.023	34.698	<0.023	31.583
2	1024	<0.023	6.056	<0.023	5.875	<0.023	8.072
	2048	<0.023	10.054	<0.023	11.058	<0.023	10.816
	4096	<0.023	14.912	<0.023	17.193	<0.023	15.961
	8192	<0.023	21.406	<0.023	25.120	<0.023	22.287
1	1024	18.569*	2.322	9.458*	2.562	<0.023	4.911
	2048	18.823*	3.050	18.846*	3.841	<0.023	6.155
	4096	<0.023	3.755**	<0.023	4.796	<0.023	8.335
	8192	<0.023	6.836	<0.023	9.991	<0.023	11.435
0.4	1024	22.383*	2.370	10.637*	2.472	22.587*	4.296
	2048	10.451*	2.711	7.871*	2.449	20.819*	3.178
	4096	50.796*	2.890	13.426*	2.826	<0.023	4.852
	8192	74.265*	3.030	74.515*	3.566	<0.023	4.484**

Equations (7)–(9) show that the following ratio takes place

$$I(N, f) \in [1, \sqrt{N}] \forall f(N),$$

$$I(N, f) = \frac{\max(f(N))}{\text{RMS}(f(N))},$$

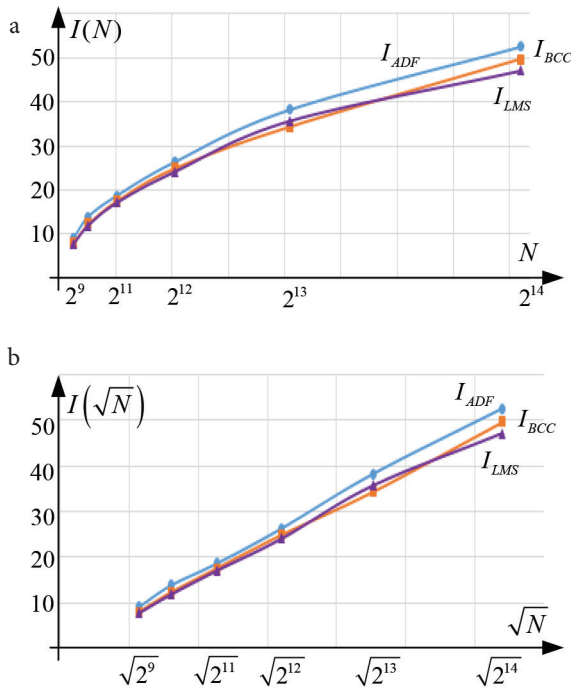
where  $N$  is the number of discrete samples in function  $f(N)$ .

At the same time, any values of  $I(N, f) < 4$  can be considered equivalent based on the results of the study. They typically indicate

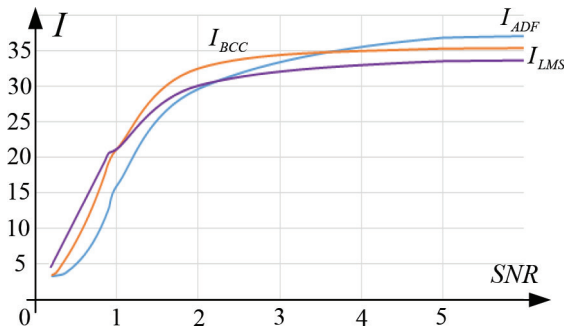
that an unambiguous TDE by the peak value of the function is impossible.

Similarly, any values of  $I(N, f) > 8$  can be considered equivalent for the opposite reason. The change in  $I(N, f)$  in the range from 4 to 8 is further considered as a metric for evaluating the influence of noise on the compared methods. The general character of empirical dependence  $I(N, f) \propto \sqrt{N}$  is reflected in Figure 9b.

The dependence in Figure 10 allows establishing the advantage of the LMS method comparing the mutual position of the curves in region  $4 < I(N, f) < 8$ .



**Figure 9** | Peak-to-mean ratio of the estimator’s output signal (a) linear scaling of the independent variable; (b) square root scaling of the independent variable.



**Figure 10** | Peak-to-mean ratio of the estimator’s output signal (curves are smoothed).

The main outcomes of the comparison are as follows:

- implementation of the ADF minimizing algorithm is simple and does not require multiplication operations. The disadvantage is the high noise sensitivity which limits the practical application of the algorithm;
- the BCC algorithm is distinguished by relatively good noise resistivity and presence of efficient computational schemes realized via the fast Fourier transforms;
- the TDE method using an adaptive LMS filter has a high noise resistance and flexibility in respect to the size of the input data. These advantages make the method applicable in the absence of a priori information about the signals. At the same time, ensuring convergence requires solving the additional problem of choosing parameter  $\mu$ .

It is notable that for implementation of correlation TDE methods the convolution theorem [16] is normally used instead

of Eq. (4). This measure provides better processing time for all  $N > 128$  [16].

The correlation methods applicability potential is also determined by the possibility of using the generalized cross-correlation algorithms, which in most cases can increase the accuracy of TDE [10,21] without a significant increase in computational complexity.

Another modification of correlation TDE methods is the time-frequency correlation analysis described in Ref. [32]. The advantage of the time-frequency approach is the ability to display visually both the frequency and time features of the analyzed signals [33]. The use of the time-frequency correlation method in leaks detection makes the correlation peaks more clear and the analysis more informative [32,33].

## 5. CONCLUSION

In the paper, the basic classes of TDE methods have been investigated, and some basic time-domain correlation and non-correlation algorithms have been compared with reference to the particular problem of determining the pipeline leak location.

In respect to the presented classification of TDE methods, a variety of methods was discussed. Among the class of passive TDE approximation methods, three basic algorithms were compared. All the algorithms with data segmentation and averaging were proposed and described in detail.

Comparative study of the algorithms was performed on model-generated signals. The leak noise model is based on noise-like signals which were applied to pipe filters. Despite the discussed limitations of the model, it is applicable for qualitative simulation of the leak noise.

The comparison was based on formal criteria of measuring the information value of the TDE functions as well as on the accuracy of estimation. Peak-to-mean values were considered to be a quantitative measure of the function’s information value. The proposed criteria have proved to be relevant for formal comparison of TDE.

The performance of three TDE algorithms was studied for various SNR and sizes of data segments. The ADF minimizing algorithm shows the lowest noise tolerance and should not be used for processing noisy signals. However, for signals with decent SNR, the ADF minimizing algorithm shows results that are comparable to other TDE algorithms under study.

Some advantages of correlation algorithms were stated, in particular, satisfactory resistance to the random noise influence, computational efficiency, and implementation simplicity. At the same time, despite the complexity of the practical application, the LMS TDE method has proved efficient in dealing with intense additive noises.

## CONFLICTS OF INTEREST

The authors declare they have no conflicts of interest.

## REFERENCES

[1] A. O’Dwyer, Time delay estimation in signal processing applications: an overview, IT & T Conference, Waterford Institute of Technology, 2002, pp. 1–6.



- [2] J. Kozłowski, Z. Kowalczyk, On-line parameter and delay estimation of continuous-time dynamic systems, *Int. J. Appl. Math. Comput. Sci.* 25 (2015), 223–232.
- [3] H.V. Fuchs, R. Riehle, Ten years of experience with leak detection by acoustic signal analysis, *Appl. Acoust.* 33 (1991), 1–19.
- [4] S. Björklund, A survey and comparison of time-delay estimation methods in linear systems, Linköpings universitet, Linköpings, Sweden, 2003.
- [5] A. Quazi, An overview on the time delay estimate in active and passive systems for target localization, *IEEE Trans. Acoust. Speech Signal Process.* 29 (1981), 527–533.
- [6] Q. Li, W. Xia, Y. Zhang, X. Jing, Z. He, A hardware design for time delay estimation of TDOA, 2013 IEEE International Conference on Signal Processing, Communication and Computing (ICSPCC), IEEE, KunMing, China, 2013, pp. 1–3.
- [7] A. Hero, H. Messer, J. Goldberg, D.J. Thomson, M.G. Amin, G. Giannakis, et al. Highlights of statistical signal and array processing, *IEEE Signal Process. Mag.* 15 (1998), 21–64.
- [8] G. Carter, Time delay estimation for passive sonar signal processing, *IEEE Trans. Acoust. Speech Signal Process.* 29 (1981), 463–470.
- [9] P. Kumar, S. Singh, Comparative study of various time delay estimation schemes using Matlab, *Int. J. Eng. Manage. Res.* 5 (2015), 322–325.
- [10] M.J. Brennan, Y. Gao, P.F. Joseph, On the relationship between time and frequency domain methods in time delay estimation for leak detection in water distribution pipes, *J. Sound. Vib.* 304 (2007), 213–223.
- [11] A. Piersol, Time delay estimation using phase data, *IEEE Trans. Acoust. Speech Signal Process.* 29 (1981), 471–477.
- [12] B. Nestleroth, S. Flamberg, W. Condit, J. Matthews, L. Wang, A. Chen, Field Demonstration of Innovative Condition Assessment Technologies for Water Mains: Leak Detection and Location, U.S. Environmental Protection Agency, Washington, DC, 2012, EPA Report no. EPA/600/R-12/018.
- [13] G. Carter, C. Knapp, A. Nuttall, Estimation of the magnitude-squared coherence function via overlapped fast Fourier transform processing, *IEEE Trans. Audio Electroacoust.* 21 (1973), 337–344.
- [14] Y. Ma, Y. Gao, B. Liu, J. Yang, Investigation into an adaptive leak detection method in water distribution pipes, Proceedings of the 24th International Congress on Sound and Vibration (ICSV), International Institute of Acoustics & Vibration, London, 2017, pp. 1–8.
- [15] Y. Wen, P. Li, J. Yang, Z. Zhou, Adaptive leak detection and location in underground buried pipelines, *Int. J. Inf. Acquis.* 1 (2004), 269–277.
- [16] E.C. Ifeachor, B.W. Jervis, *Digital Signal Processing: A Practical Approach*, second ed., Prentice Hall, Upper Saddle River, NJ, 2001.
- [17] S.M. Kuo, B.H. Lee, W. Tian, *Real-Time Digital Signal Processing: Implementations and Applications*, Wiley, New York, 2001.
- [18] E. Mytsko, A. Malchukov, S. Ryzova, V. Kim, A study of hardware implementations of the CRC computation algorithms, *MATEC Web of Conf.* 48 (2016), 04001.
- [19] S.M. Kuo, W.S. Gan, *Digital Signal Processors: Architectures, Implementations, and Applications*, Pearson Prentice Hall, New Delhi, 2004.
- [20] C. Knapp, G. Carter, The generalized correlation method for estimation of time delay, *IEEE Trans. Acoust. Speech Signal Process.* 24 (1976), 320–327.
- [21] R. Ionel, S. Ionel, P. Bauer, F. Quint, Water leakage monitoring education: cross correlation study via spectral whitening, IECON 2014 - 40th Annual Conference of the IEEE Industrial Electronics Society, Dallas, Texas, 2014, pp. 2465–2471.
- [22] Y. Chan, R. Hattin, J. Plant, The least squares estimation of time delay and its use in signal detection, *IEEE Trans. Acoust. Speech Signal Process.* 26 (1978), 217–222.
- [23] M. Omologo, P. Svaizer, Acoustic event localization using a crosspower-spectrum phase based technique, Proceedings of ICASSP '94. IEEE International Conference on Acoustics, Speech and Signal Processing, Adelaide, South Australia, 1994, pp. 273–276.
- [24] Z. Zhen, H. Zi-qiang, The generalized phase spectrum method for time delay estimation, ICASSP '84. IEEE International Conference on Acoustics, Speech, and Signal Processing, San Diego, CA, USA, 1984, pp. 459–462.
- [25] V.A. Zhmud, A.M. Goncharenko, Modern problems of high-precision measurements of the phase differences, 13th International Scientific-Technical Conference on Actual Problems of Electronics Instrument Engineering (APEIE), Novosibirsk, Russia, 2016, pp. 314–318.
- [26] V.A. Vasil'ev, V.A. Zhmud', Y.N. Il'yanovich, V.M. Semibalamut, Y.N. Fomin, Detection of the increment of an instantaneous phase in a long-base laser meter of small vibrations, *Instrum. Exp. Tech.* 45 (2002), 526–529.
- [27] D.A. Terentiev, A.A. Firsov, Algorithm based on phase cross-spectrum analysis for improving the accuracy of leak-noise correlators [Algoritm povysheniya tochnosti lokacii pri korreljacionnom techeiskanii, osnovannyj na analize fazy vzaimnogo spektra], *Nondestruct. Test. Control* 8 (2014), 23–27 (in Russian).
- [28] A.S. Papastefanou, P.F. Joseph, M.J. Brennan, Experimental investigation into the characteristics of in-pipe leak noise in plastic water filled pipes, *Acta Acust. united Acust.* 98 (2012), 847–856.
- [29] M.J. Brennan, F. Kroll de Lima, F.C.L. de Almeida, P.F. Joseph, A.T. Paschoalini, A virtual pipe rig for testing acoustic detection correlators: proof of concept, *Appl. Acoust.* 102 (2016), 137–145.
- [30] V.A. Faerman, A.V. Tsavnin, Concept and implementation of the laboratory test bench for simulating the case of leak detection with the use of leak-noise correlator, Proceedings of Russian conference on Development and Debugging of Complex Engineering Systems, Moscow, Russia, 2019.
- [31] V.I. Goncharov, A.A. Yefremov, V.S. Avramchuk, New calculation method of correlation function applied to leak localization, 2014 International Conference on Mechanical Engineering, Automation and Control Systems (MEACS), Tomsk, Russia, 2014, pp. 1–4.
- [32] V.S. Avramchuk, V.I. Goncharov, Time-frequency correlation method for improving the accuracy in detecting leaks in pipelines, *Adv. Mater. Res.* 650 (2013), 443–446.